

Optimized Utilization of Longitudinal MRI in Deep-learning-based Survival Prediction of Alzheimer’s Disease Progression

Ferial Delavari · Sophia Kyriacou · Yinting Liu · Timothy Hohman PhD · Shannon Risacher PhD · Marc D Rudolph · Suzanne Craft · Metin N Gurcan · Da Ma

Wake Forest University School of Medicine · Georgia Tech · NYU · Vanderbilt University Medical Center

INTRODUCTION

BACKGROUND

Alzheimer's disease progression from MCI to AD follows a gradual trajectory detectable in structural MRI. Survival analysis provides a principled framework for modeling time-to-conversion, yet the value of repeated MRI visits and explicit temporal modeling remains poorly understood.

THE GAP

Prior deep learning survival models treat longitudinal data as static snapshots or simple concatenations ; failing to capture how brain structure evolves over time.

RESEARCH QUESTION

How does incorporating multiple MRI visits and temporal architecture design influence survival-based risk estimation for AD conversion?

CONTROLLED DESIGN

All models share the same Cox PH survival loss and evaluation protocol, isolating the pure effect of temporal architecture.

Acknowledgments

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METHODS

DATASET & FEATURES

SUBJECTS

777 ADNI participants, up to 3 MRI visits

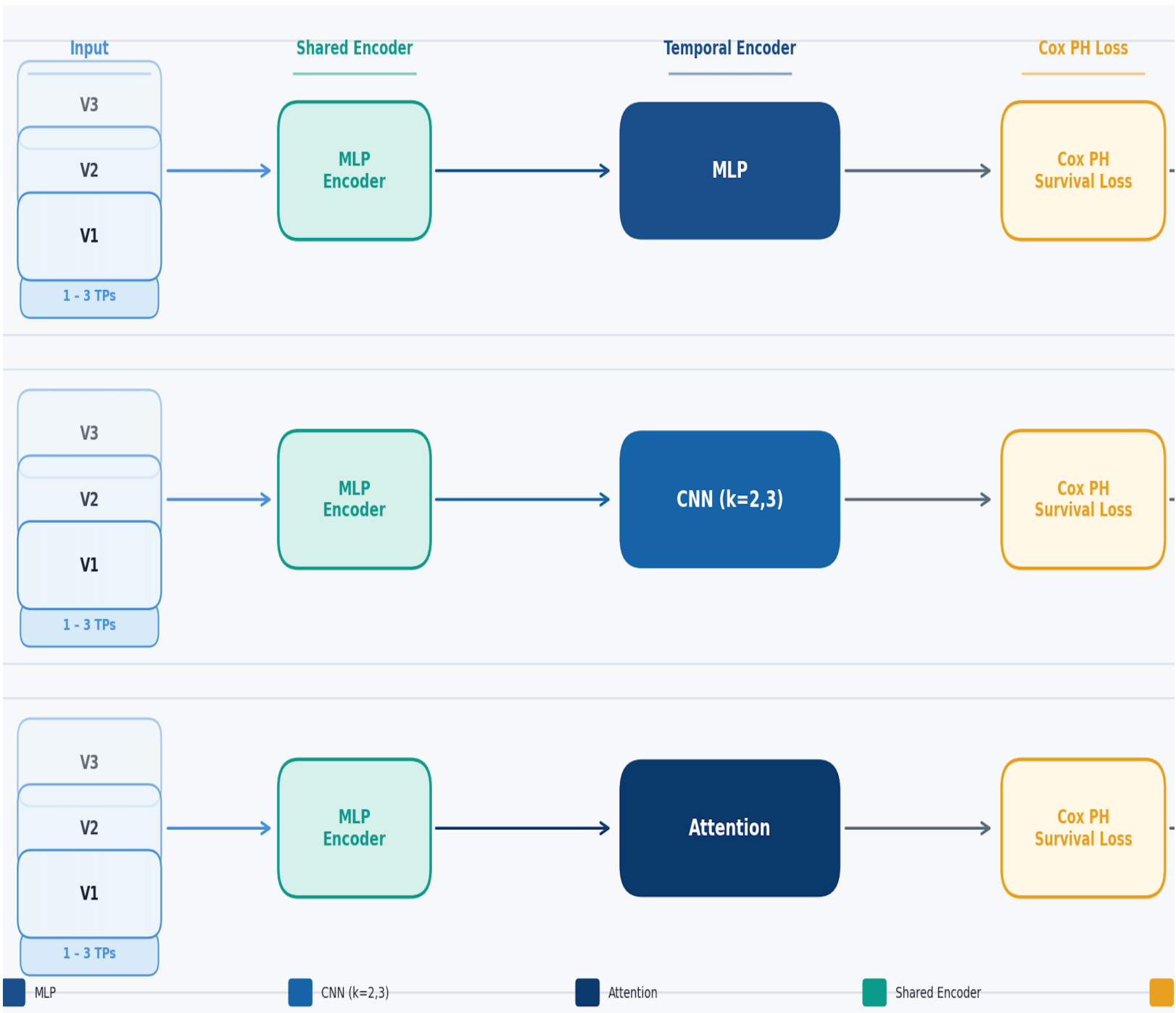
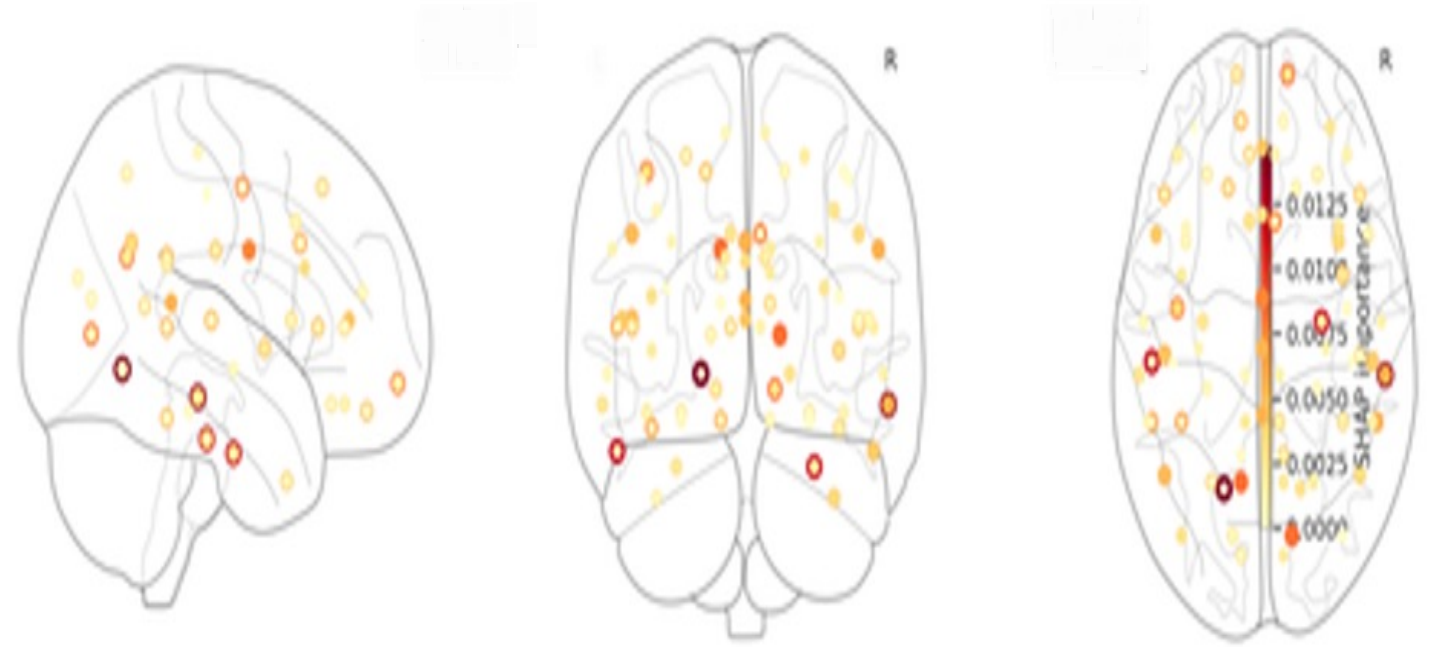
FEATURES

192 FreeSurfer volumes/visit, ComBat harmonized

METRICS

C-index: measures ranking accuracy
IBS: measures calibration ; how well do predicted probabilities match actual outcomes over time?
ΔT: predicted minus actual conversion time in years.

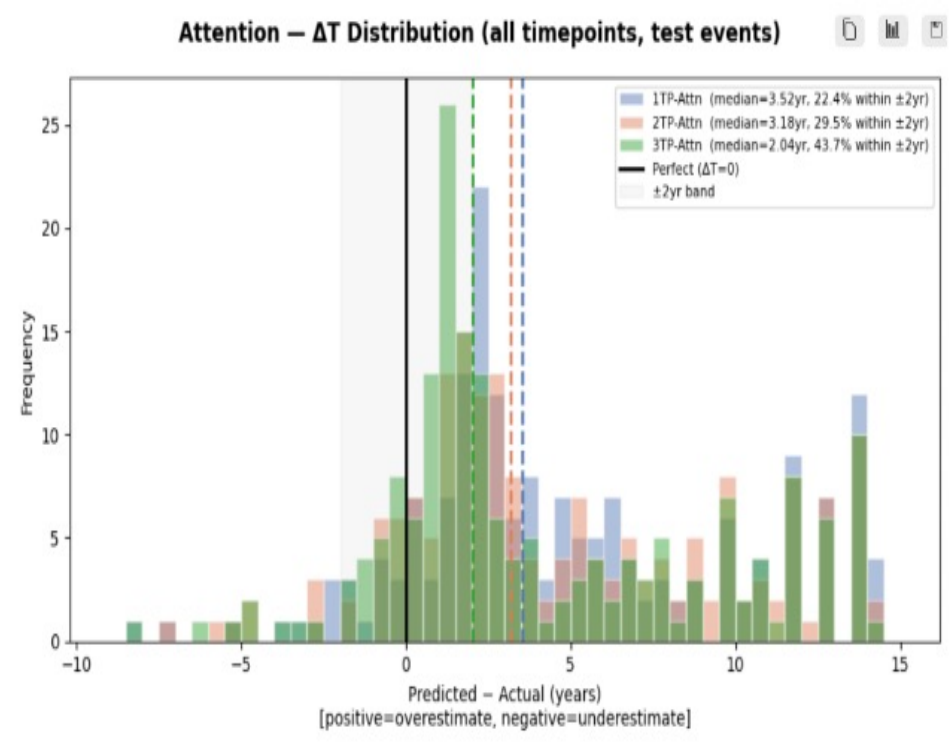
ARCHITECTURES



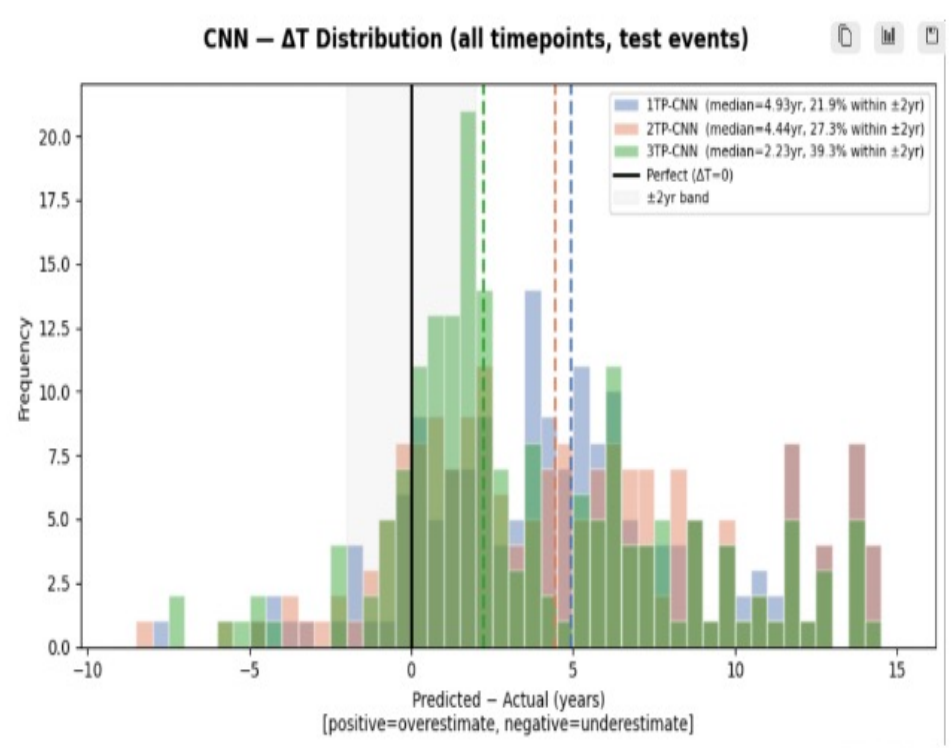
RESULTS

C-INDEX BY MODEL & TIMEPOINTS

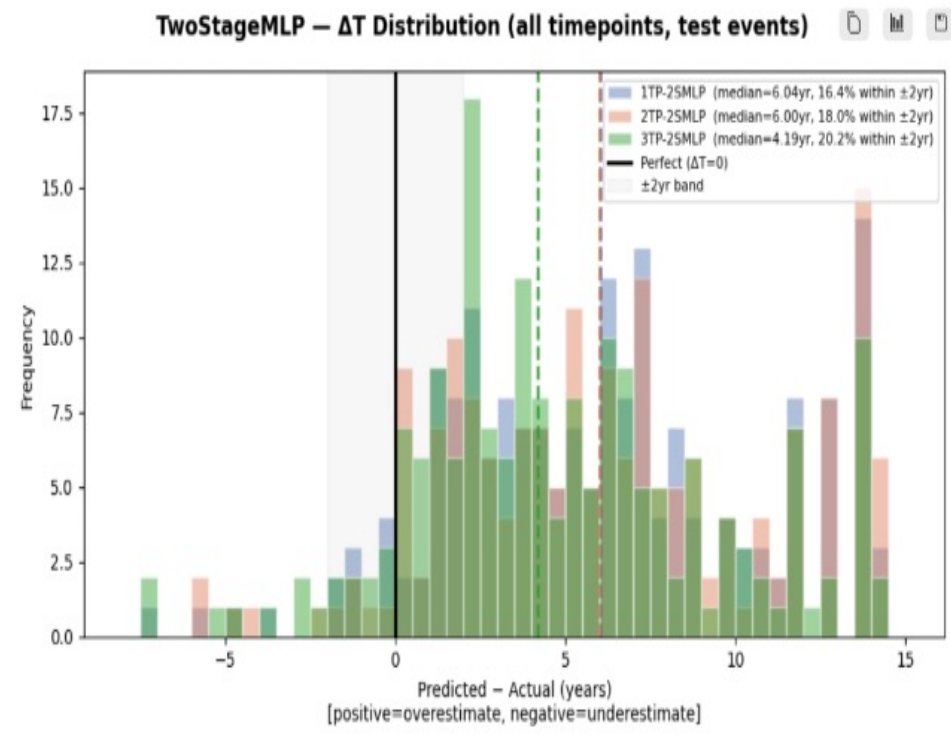
Model	TP	Mean K fold C-index
MLP	1	0.695
MLP	2	0.793
MLP	3	0.801
Attention	2	0.817
Attention	3	0.824
CNN k=2	2	0.804
CNN k=2	3	0.813
CNN k=3	2	0.819
CNN k=3	3	0.825



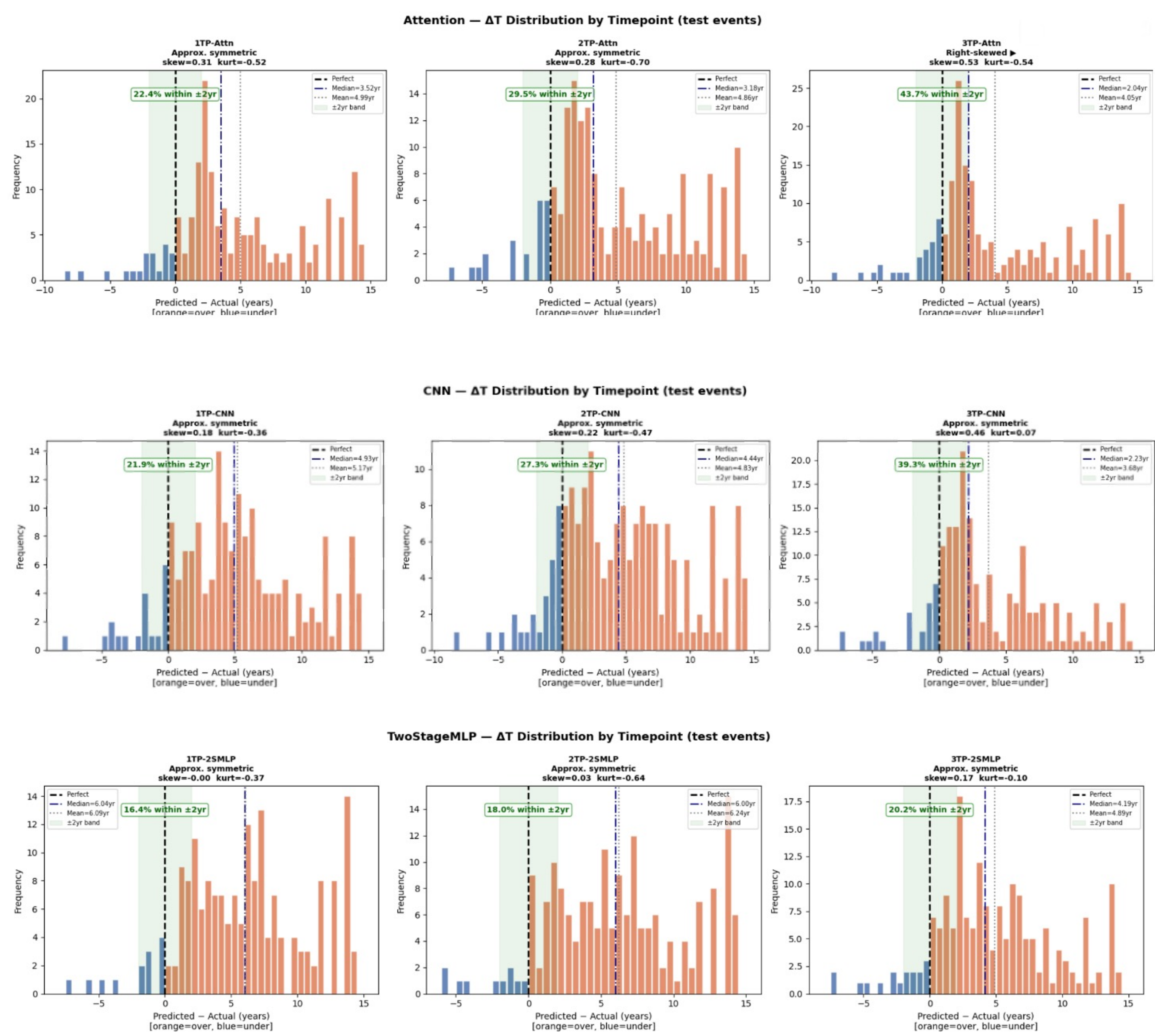
Attention: median ΔT 3.5 → 2.0 yrs with added timepoint



CNN k=3 and MLP: 100% of predictions within ±12 years



Mean error drops from 5.9 yrs (MLP, 1 TP) to 2.1 yrs (CNN k=3, 3 TPs)



CONCLUSIONS

✓ More timepoints = better survival prediction ; C-index rises consistently from 1 to 3 visits across all architectures

✓ Temporal modeling captures disease trajectory ; CNN and Attention learn progression patterns that simple concatenation cannot

✓ Attention model is the best calibrator ; lowest IBS (0.142) and lowest mean ΔT (2.1 yrs), predicting conversion timing most precisely

FUTURE DIRECTIONS

→ Interpretability: map hippocampal & entorhinal contributions across timepoints via attention maps

References

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2. Mirabnahrasm G, Ma D, Beaulac C, Lee S, Popuri K, Lee H, Cao J, Galvin JE, Wang L, Beg MF; Alzheimer's Disease Neuroimaging Initiative. Predicting time-to-conversion for dementia of Alzheimer's type using multi-modal deep survival analysis. Neurobiol Aging. 2023 Jan;121:139-156. doi: 10.1016/j.neurobiolaging.2022.10.005. Epub 2022 Oct 17. PMID: 36442416; PMCID: PMC10535369.